Cross–Sectoral Variation in Firm–Level Idiosyncratic Risk*

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Abstract

We estimate firm–level idiosyncratic risk in the U.S. manufacturing sector. Our proxy for risk is the volatility of the portion of growth in sales or TFP which is not explained by either industry– or economy–wide factors, or firm characteristics systematically associated with growth itself. We find that idiosyncratic risk accounts for about 90% of the overall uncertainty faced by firms. The extent of cross–sectoral variation in idiosyncratic risk is remarkable. Firms in the most volatile sector are subject to at least three times as much uncertainty as firms in the least volatile. Our evidence indicates that idiosyncratic risk is higher in industries where the extent of creative destruction is likely to be greater.

Key words: Schumpeterian Competition, Creative Destruction, Product Turnover, R&D Intensity, Investment–Specific Technological Change.

JEL Codes: D24, L16, L60, O30, O31.

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1 Introduction

The main goal of this study is to assess the cross–sectoral variation in firm–level idiosyncratic risk in U.S. manufacturing. Our data consists of a large panel extracted from the U.S. Census' Longitudinal Research Database (LRD).

We proxy idiosyncratic risk with the portion of the variation in growth (in sales or TFP) that is not accounted for by aggregate disturbances or by other factors that vary systematically with growth, such as age and size.

Our manufacturing–wide estimates suggest that idiosyncratic risk is substantially larger than aggregate risk. The volatility of annual sales growth is about 10%, while the volatility of TFP growth is roughly 8%. As a term of comparison, notice that between WWII and the great moderation the standard deviation of U.S. annual real GDP growth was only 2.52%.

The variation in idiosyncratic risk across three–digit industries is substantial. To gain a flavor of the amount of heterogeneity we uncover, consider that the volatility of sales growth ranges from 3.78% for publishers of newspapers to a whopping 18.53% for manufacturers of railroad equipment.

Why does volatility differ so much across sectors? We provide some preliminary evidence in favor of a particular explanation: volatility is higher in sectors where creative destruction is more important.

The notion of creative destruction is central to the Schumpeterian paradigm. According to the latter, firms are engaged in a perpetual race to innovate. Creation, i.e. the success by a laggard in implementing a new process or producing a new good, displaces the previous market leader, eliminating (destroying) its rent.

Formal models of Schumpeterian competition[1] predict a positive cross–sectoral association between creative destruction, product turnover, and innovation–related activities. We document that idiosyncratic risk is higher in industries where product turnover is greater and investment–specific technological progress is faster.

Learning about the magnitude of firm–level idiosyncratic risk is important in light of the remarkable role that the latter plays in many areas of applied economics. In Hopenhayn (1992) and Ericson and Pakes (1995), two of the most popular frameworks for the study of industry dynamics, as well as in theories of financing constraints based on asymmetric information, such as Clementi and Hopenhayn (2006) and Quadrini (2003), firms are modeled as risk–neutral agents facing sequences of idiosyncratic

[1] We refer to the economic growth literature that builds on Aghion and Howitt (1992).

shocks.

Given that firms' stakeholders have often limited insurance opportunities, assessing firm–level risk is also relevant for the analysis of scenarios where risk aversion matters. This is the case of entrepreneurship studies such as Quadrini (1999), theories of economic development such as Castro, Clementi, and MacDonald (2004, 2009), and models of innovation such as Caggese (2008).

The evidence of lack of diversification abounds. Clementi and Cooley (2009) document that in 2006, more than 20% of CEOs of U.S. publicly–traded concerns[2] held more than 1% of their companies' common stock. About 10% held more than 5%. Given the large capitalization of such companies, this information points to limited portfolio diversification for these individuals. Herranz, Krasa, and Villamil (2009) find that 2% of the primary owners of the firms sampled by the 1998 Survey of Small Business Finance[3] invested more than 80% of their personal net worth in their firms; 8% invested more than 60%, and about 20% invested more than 40%.

We are not the first to realize the need of assessing risk at the firm level. Campbell, Lettau, Malkiel, and Xu (2001) proxied risk with the volatility of excess stock returns. They decomposed the latter in three components: aggregate, industry–wide, and firm–level. This allowed them to obtain average measures of idiosyncratic risk for the whole economy and for several coarsely defined sectors.

Our view is that their methodology delivers reasonable proxies for the risk borne by equity investors, but not for that faced by other stakeholders, such as the owners of small firms. This is the case for three reasons. First of all, COMPUSTAT only includes publicly traded companies, and therefore is not representative of the universe of firms in the U.S. Second, their measure of firm–level volatility clearly depends on the volatility of the stochastic discount factor and on the covariance of the latter with cash flows. Finally, the cash flows are those expected to accrue to equity investors. This implies, for example, that they are affected by leverage.

Our exercise is closer to those carried out in more recent papers, that exploit balance sheet information rather than stock market data. We refer to the contributions of Abraham and White (2006), Bachman and Bayer (2009), and Gourio (2008), who estimate processes for idiosyncratic risk using unbalanced panels from the U.S. Cen-

[2]The data is from EXECUCOMP, a proprietary database maintained by Standard & Poor's that contains information about compensation of up to 9 executives of all companies quoted in organized exchanges in the U.S.

[3]The SSBF, administered by the Board of Governors of the Federal Reserve System, surveys a large cross–sectional sample of non–farm, non–financial, non–real estate firms with less than 500 employees.

sus' LBD, Deutsche Bundesbank's USTAN, and Compustat, respectively. We also think of the work by Comin and Mulani (2006), Comin and Philippon (2005), and Davis, Haltiwanger, Jarmin, and Miranda (2006).

Our study is different from all the above, in that it illustrates the cross–sectoral variation in firm–level idiosyncratic uncertainty. We provide estimates of risk by three–digit SIC sectors and make a first attempt at identifying the determinants of the heterogeneity we uncover.

Understanding how idiosyncratic risk varies across industries is a necessary step towards the quantitative evaluation of a recent breed of multi–sector models, such as Castro, Clementi, and MacDonald (2009), Cuñat and Melitz (2010), and Caggese (2008). According to the first two, cross–sectoral differences in idiosyncratic risk, together with cross–country heterogeneity in institutions, rationalize the observed cross–country variation in relative price of capital goods and investment rate (the former), and trade specialization (the latter). Caggese (2008) studies the impact of idiosyncratic risk on entrepreneurial firms' propensity to innovate.

To our knowledge, four other studies set out to characterize the extent of cross–sectoral variation in firm–level volatility. Michelacci and Schivardi (2008) use a methodology close to Campbell, Lettau, Malkiel, and Xu (2001). Castro, Clementi, and MacDonald (2009) and Cuñat and Melitz (2010) estimate the volatility of sales growth in COMPUSTAT. Chun, Kim, Mork, and Yeung (2008) find that, for COMPUSTAT firms, the heterogeneity of firm–specific stock returns and sales growth is higher in 2–digit SIC sectors that use information technology more intensively.

The gain from using the LRD in place of COMPUSTAT is substantial. To start with, the LRD is a much larger sample. This allows us to work with a finer sector classification. Furthermore, the sampling technique ensures that the LRD is representative of the population of manufacturing firms. Since COMPUSTAT only covers companies whose stock is traded in an organized exchange, it is severely biased towards large firms.

Finally, the better quality of the data on investment allows us to compute reliable estimates of TFP growth. The conditional volatility of sales growth is not the ideal proxy for idiosyncratic risk because swings in a firm's sales depend not only on the shocks, which size we are interested in measuring, but also on the firm's ability to alter its inputs to accommodate them. The volatility in firm–level TFP growth is exempt from this criticism.

The remainder of the paper is organized as follows. The data and methodology are described in Section 2. Our volatility estimates across three–digit industries are illustrated in Sections 3. In Section 4 we illustrate evidence in support of the conjecture that idiosyncratic risk is greater in industries where creative destruction is more important. In Section 5 we show that, consistent with what found by Castro, Clementi, and MacDonald (2009) for public firms, firms that produce capital goods are systematically riskier than their counterparts producing consumption goods. Finally, Section 6 concludes.

2 Data and Methodology

2.1 Data

Our data is from the Annual Survey of Manufactures (ASM) portion of the Longitudinal Research Database (LRD) for the years 1972 through 1997. Depending on the year, its size varies from 50,000 to 70,000 establishments, distributed among 140 three–digit SIC manufacturing industries. With the ASM weights, our sample ends up being representative of the entire U.S. manufacturing sector.

Our unit of observation is the establishment, defined as the minimal unit where production takes place. This is obviously short of ideal, as multi–plants firms may change the assignment of production to manufacturing units in response to shocks. In the remainder, we will use the terms *plant* and *firm* interchangeably.

Using the LRD rather than COMPUSTAT has a variety of advantages. To start with, our results are not subject to the selection bias emphasized by Davis, Haltiwanger, Jarmin, and Miranda (2006), who document a behavior of public firms markedly different from that of private firms, absent in COMPUSTAT. Furthermore, the LRD allows for a finer level of disaggregation. Our analysis is at the three–digit SIC sectoral level, which maps into four– and five–digit NAICS. Working with COMPUSTAT, Castro, Clementi, and MacDonald (2009) could not go finer than three–digit NAICS. Finally, the LRD allows us to compute reliable estimates of firms' capital stocks, which is necessary to compute Solow residuals.

For our purposes, the only drawback of the LRD is that it only covers manufacturing firms, whereas COMPUSTAT spans all sectors.[4]

Real sales are the nominal value of shipments, deflated using the four–digit industry–specific deflator from the NBER manufacturing productivity database. Size is measured by the number of employees, whereas age is the time since the establishment

[4]The Census Bureau's Longitudinal Business Database (LBD) has a broader coverage. However, since it does not contain information on capital stocks, it is not suited to computing firm–level TFP.

went into operation.[5]

Following Foster, Haltiwanger, and Krizan (2001), Baily, Hulten, and Campbell (1992), and Syverson (2004), we define TFP levels as firm–level Solow residuals. The (log) Solow residual for firm i in sector j at time t is

$$\ln z_{ijt} = \ln y_{ijt} - \alpha_j^k \ln k_{ijt} - \alpha_j^\ell \ln \ell_{ijt} - \alpha_j^m \ln m_{ijt},$$

where y_{ijt} is shipments, k_{ijt} is capital, ℓ_{ijt} is labor, and m_{ijt} is materials. The elasticities α_j^k, α_j^ℓ and α_j^m are assumed to be sector–specific. As in the literature just cited, we set them equal to narrowly–defined sectoral input cost shares. For further details, see Appendix A.1.

Notice that changes in our measures of real sales and TFP reflect not only fluctuations in quantities, but also within–industry price variation. Our TFP measure is what has become known in the literature as real revenue per unit input, or TFPR. This definition is perfectly suited for our study, as we are interested in identifying all sources of idiosyncratic uncertainty, including price variation.

2.2 Methodology

The methodology is going to be the same for either measure of firm growth, based on either sales or TFP. For convenience, we describe it in the case of sales. First, we estimate

$$\Delta \ln(sales)_{ijt} = \mu_i + \delta_{jt} + \beta_{1j} \ln(size)_{ijt} + \beta_{2j} Age_{ijt} + \varepsilon_{ijt}. \tag{1}$$

The dependent variable is the growth rate of real sales for firm i in sector j, between years t and $t+1$. The dummy variable μ_i is a firm–specific fixed effect that accounts for unobserved persistent heterogeneity across firms. The variable δ_{jt} denotes a full set of sector–specific year dummies, which control for changes in sales induced by sector–specific shocks and cross–sectoral differences in business cycle volatility. We include size and age because both were shown to be negatively correlated with firm growth.[6]

Regression (1) computes the systematic, or predictable component of sales growth. Any variation in sales growth not due to systematic factors is captured by the estimated residuals $\hat{\varepsilon}_{ijt}$. These are the objects of interest, since they are interpreted as realizations of firm–specific shocks.

[5] In our regression analysis, we follow Davis, Haltiwanger, and Schuh (1996) in that we use 3 categories of age dummies: Young, Middle-Aged, and Mature.

[6] See Hall (1987) and Evans (1987).

The second step consists in measuring how the standard deviation of such shocks varies across sectors. This is accomplished by fitting a simple log–linear model to the variance of residual sales growth:

$$\ln \hat{\varepsilon}^2_{ijt} = \theta_j + v_{ijt}, \tag{2}$$

where θ_j is a sector–specific dummy variable. Letting $\hat{\theta}_j$ denote its point estimate, $\sqrt{\exp(\hat{\theta}_j)}$ is our measure of the conditional standard deviation of sales growth for firms in sector j.

3 Volatility Estimates

The mean standard deviation of annual sales growth across all manufacturing plants is 10.07%. As expected, the standard deviation of TFP growth is lower, at 8.05%. The reason is that changes in sales accompanied by changes in inputs in the same direction result in smaller changes in TFP (in absolute value).

Our estimates suggest that idiosyncratic risk is substantially larger than aggregate risk. This can be appreciated by comparing them with readily available measures of aggregate volatility. The average standard deviation of U.S. annual real GDP growth was 2.52% before the great moderation (i.e. in the period 1950–1978) and fell to 1.75% in the period 1979–2007.

A more formal way of assessing the importance of idiosyncratic risk Vs. aggregate risk is to compare the former with more comprehensive measures of firm–level uncertainty, which also reflect the portion that may be ascribed to industry–wide and economy–wide factors. Such measures can be calculated by regressing log–sales (or log–TFP) on firm fixed effects only and computing the standard deviation of the residuals.

This exercise yields volatility estimates that are only marginally greater than our measures of idiosyncratic risk. The overall volatility of sales growth is estimated to be 11.58%. That of TFP growth is 9.45%. Idiosyncratic factors appear to account for about 90% of overall firm–level uncertainty.

Our volatility estimates across three–digit industries are reported in Table 5 and illustrated in Figure 1. The height of each bin is the fraction of sector whose estimated risk falls in the associated interval.

The range of estimates is rather wide, no matter the proxy. The volatility of sales growth is as low as 3.78% for Newspaper Publishing (SIC 271) and as high as 18.53% for Railroad Equipment (374). The volatility of TFP growth is lowest in the Fur

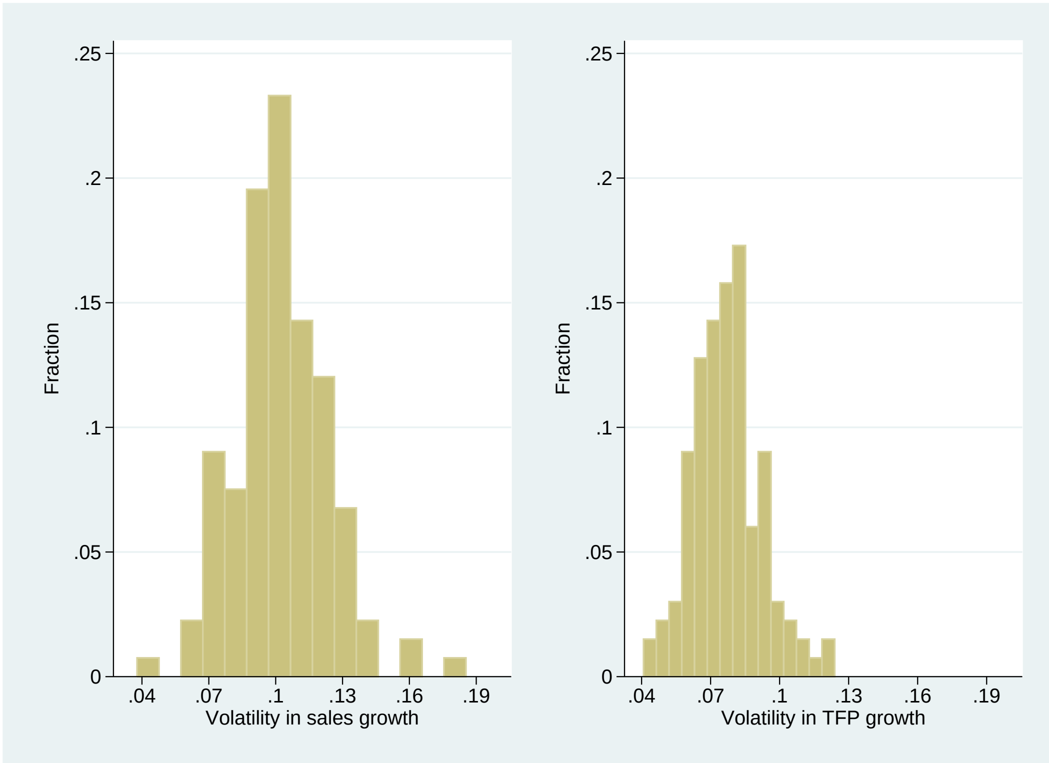

Figure 1: Histogram of idiosyncratic risk by sector.

Goods sector (237), at 4.09%, and highest in Computer Equipment Manufacturing (357), at 12.39%.

The orderings delivered by the two measures are fairly consistent. The Spearman's rank–correlation coefficient is 0.71.

Drawing comparisons between our estimates of sales growth volatility and those recovered by Castro, Clementi, and MacDonald (2009) (CCM from now on) for public companies is interesting, but is subject to a couple of important caveats. First and foremost, our data is at the plant–level, while theirs is at the firm level. Secondly, their sector classification is at the three–digit NAICS, which is coarser than ours.

For the sectors for which a match is possible, our estimates are sensibly higher. For Computer and Electronic Product Manufacturing, CCM report an estimate of 10.52%, lower than the 15.87% we estimate for SIC 357. For Machine Manufacturing, they estimate volatility at 8.89%, a figure lower than our estimates for all sectors producing machinery (SIC 352, 354, 355, 356, and 358). Similarly, their 4.9% estimate for Food Manufacturing is lower than our estimates for the three–digit SIC sectors that belong to that industry (SIC 201 through 207 plus 209).

This pattern is consistent with the findings of Davis, Haltiwanger, Jarmin, and Miranda (2006), who compare the volatility of public Vs. privately held firms, and with the industrial organization literature that documents the negative correlation between growth volatility and size.

4 Creative Destruction and Volatility

Why does volatility differ so much across sectors? In this section, we look for evidence in favor of a particular explanation: volatility is higher in sectors where the speed and extent of creative destruction are greater.

Joseph Schumpeter envisioned economic progress as the result of a perpetual race between innovators. Success by a laggard or an outsider in implementing a new process or producing a new good, provides them with a competitive advantage and displaces the previous market leader, eliminating its rent. This, in a nutshell, is the process of creative destruction.

We conjecture that most of the firm–level volatility that we document reflects the turnover between market participants which is at the center of Schumpeter's paradigm. That is, we argue that a large fraction of the fluctuations in a firm' sales and TFP growth is due to variations in its distance from the technology frontier.

Our strategy consists in looking for sector–specific attributes that are likely to be systematically associated with the speed of turnover. Starting with Aghion and Howitt (1992), Schumpeter's idea was formalized in a large number of models. We turn to this literature for guidance.

In Aghion and Howitt (1992), the producer endowed with the leading technology monopolizes the intermediate good market. Technology improves as a result of purposeful research and development, which in equilibrium is only carried out by prospective entrants. When it succeeds in obtaining a new and more productive variety of intermediate good, the innovator enters and displaces the monopolist. It follows that all the variation in sales growth is associated with product turnover.

The positive association between product turnover and firm–level volatility is not specific to Aghion and Howitt (1992). Rather, it is a robust feature of all of its generalizations in which intermediate goods of different vintages are vertically differentiated. For example, see Aghion, Harris, Howitt, and Vickers (2001) and Aghion, Bloom, Bludell, Griffith, and Howitt (2005).

The race can also be among firms that are not directly engaged in R&D, but adopt components which embed innovations made by others. This is the scenario described by Copeland and Shapiro (2010), who model the personal computers industry. The adoption decision, which entails the introduction of a new product, leads to a rise in sales for the adopter, and to a decline for its competitors.

In Samaniego (2009), the decision that yields a competitive advantage is that of acquiring the latest vintage of equipment. The faster is investment–specific technological change, the more frequent is technology adoption by either laggards or new entrants. In turn, this leads to a more frequent turnover in industry leadership and more variability in sales growth.

In the next section, we ask whether product turnover is indeed higher in industries where firms are documented to face a greater volatility of sales and TFP growth. In Sections 4.2 and 4.3 we will ask whether our volatility measures are positively related with the intensity of R&D and the speed of investment–specific technological change, respectively.

4.1 Product Turnover

The U.S. Bureau of Labor Statistics collects prices on 70,000–80,000 non–housing goods and services from around 22,000 outlets across various locations. When a product is discontinued, the agency starts collecting prices of a closely related good at the same outlet, and records the substitution information. The BLS classifies goods in narrowly–defined categories known as entry–level items (ELI).

Our proxy for turnover is the average monthly frequency of substitutions, known as the item substitution rate. It is the fraction of goods in the ELI that are replaced on average every month. Our data is drawn from Bils and Klenow (2004)'s tabulations, which in turn are based on information on more than 300 consumer good categories from 1995 to 1997.[7]

Using the algorithm developed by Chang and Hong (2006), we were able to match 53 three–digit SIC manufacturing sectors with at least one ELI. For 21 sectors, the correspondence is one–to–one. The remaining 32 are matched to 213 items. In such cases, we defined the substitution rate as the average of the associated ELIs' rates, weighted by their respective CPI weights.

[7] The BLS distinguishes between two types of substitutions. Substitutions are comparable when the replacement does not represent a quality improvement over the previous item. They are noncomparable, otherwise. Since average and noncomparable average item substitution rates are highly correlated across good categories, our results did not change much when we used noncomparable item substitution rates instead.

Two caveats are worth mentioning. To start with, the BLS data focuses on consumer goods. Most investment good sectors are missing. Furthermore, the substitution rate only tells about the “frequency” of product turnover and does not provide information about the “size of the step”, i.e. the extent to which a new product improves over the pre–existing one.

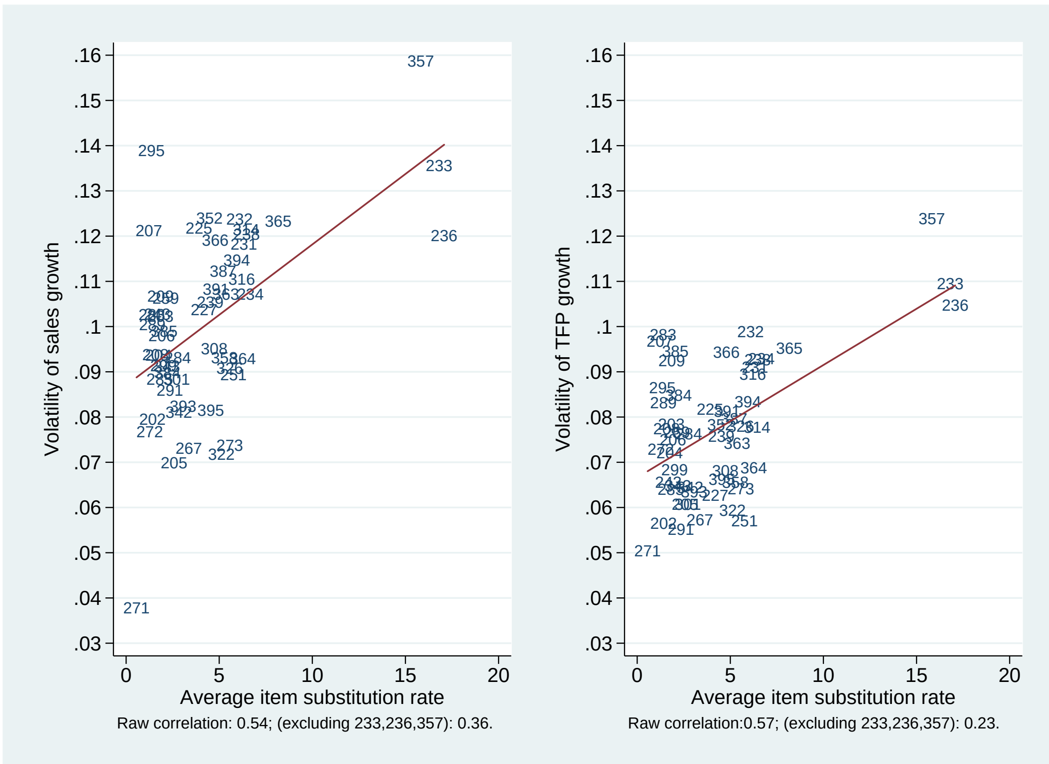

Figure 2: Idiosyncratic Risk and Product Substitution Rate.

The scatter plots in Figure 2 show that our proxy for product turnover is positively associated with both measures of volatility. The simple correlation coefficients are 0.543 and 0.571 in the cases of sales and TFP, respectively.

Three sectors stand out, as they are characterized by high volatility measures and remarkably high substitution rates. They are Computer and Office Equipment (357), Women’s and Misses’ Outerwear (233), and Girls’ and Children’s Outerwear (236). Anecdotal evidence as well as scholarly research[8] suggest that SIC 357 epitomizes the idea of creative destruction. However, product turnover in the other two sectors is not likely to be driven by technological improvements.

Idiosyncratic risk and turnover are positively associated even when we exclude

[8] See Copeland and Shapiro (2010) and citations therein.

SIC 233, 236, and 357. However, the correlation coefficients drop to 0.359 and 0.235, respectively.

The first two columns in Table 1 report the results of regressing sales growth volatility on the average substitution rate and a constant. Column (1) tells us that on average, a 1% higher substitution rate implies a 0.31% higher volatility of sales growth. In column (2) we drop SIC 233, 236, and 357. The coefficient increases slightly, but the R^2 is reduced by half.

Table 1: Idiosyncratic Risk and Product Substitution Rate.

Dependent Variable:	**Sales volatility**		**TFP volatility**	
	(1)	(2)	(3)	(4)
Substitution Rate	0.0031***	0.0034**	0.0025***	0.0016
	(0.0007)	(0.0013)	(0.0005)	(0.0009)
Constant	0.0870***	0.0862***	0.0666***	0.0697***
	(0.0038)	(0.0052)	(0.0028)	(0.0039)
Observations	53	50	53	50
R^2	0.295	0.129	0.326	0.055

Standard errors in parenthesis. ***Significant at 1%. **Significant at 5%. *Significant at 10%.

According to the results listed in column (3), on average a 1% higher substitution rate is associated with a 0.25% higher TFP growth volatility. Without SIC 233, 236, and 357 (see column (4)), the R^2 is lower. The coefficient is only marginally insignificant at the 10% confidence level (its p–value is 0.101).

Many establishments in the LRD are likely to produce more than one product. Possibly, many more. As long as the correlation between sales from different lines of business is less than 1, plant–level sales growth volatility will be lower than average volatility at the level of product line. This may explain why sectors such as Glass and Glassware (322), Books (273), and Household Furniture (251) are characterized by a relatively high item substitution rate and low volatility of both sales and TFP growth.

4.2 R&D Intensity

Unfortunately we lack data on research and development expenditure in the LRD. We measure a sector's research intensity as the ratio of R&D expenditure to sales in COMPUSTAT. The latest CENSUS–NSF R&D survey found that most of the research and development activity takes place at large firms. This leads us to think that the cross–sectoral variation in R&D expenditures in the population is not likely to differ much from that for large, public firms.

The cross–industry variation in research expenditures that we uncover is substantial. Our measure of research intensity varies from 0.022% for Book Binding (SIC 278) to 7.77% for firms in Drugs (283).

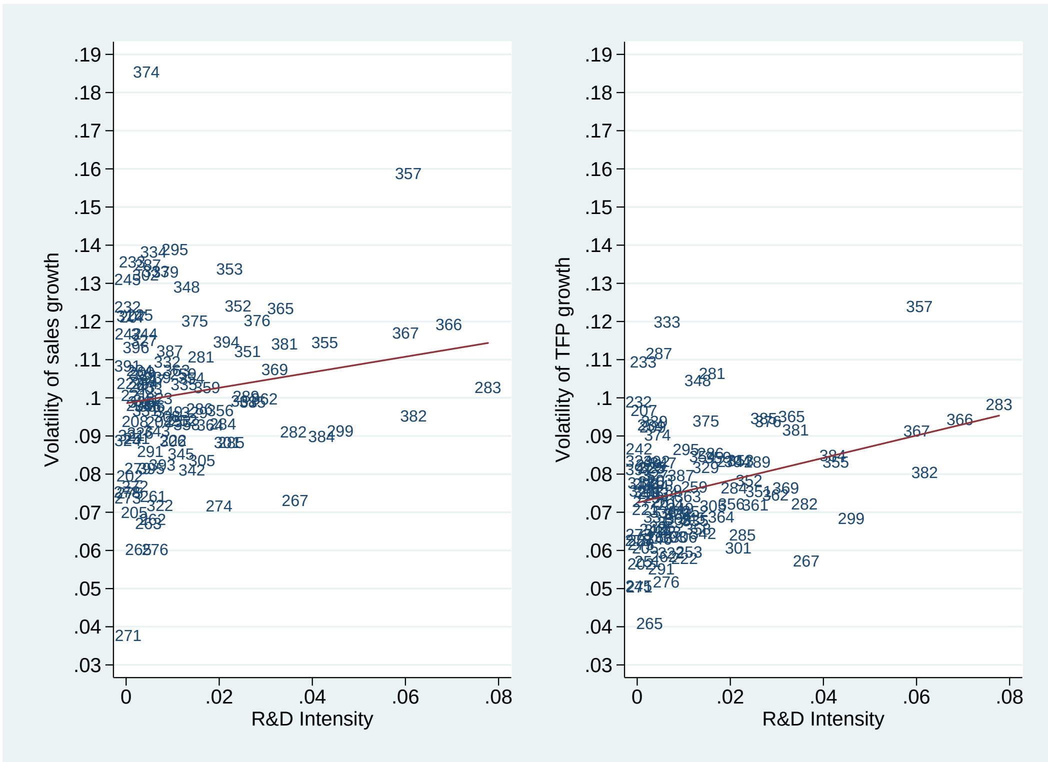

Figure 3: Idiosyncratic Risk and R&D.

The unconditional relationship between our risk proxies and research intensity is illustrated in Figure 3. In Table 2 we report the results of regressing the two volatility measures on R&D intensity and a constant. In the case of sales volatility, the coefficients are not statistically significant. In the case of TFP volatility, the coefficient of R&D intensity is statistically and economically significant. At the mean, a 1% increase in research intensity implies an increase in TFP growth volatility of about 30%.

4.3 Investment–Specific Technological Change

In a simple two–sector model where investment and consumption goods are produced competitively, the quality improvement in the investment good equals the negative

Table 2: Idiosyncratic Risk and Research Intensity.

Dependent Variable:	Sales volatility	TFP volatility
R&D Intensity	0.2033	0.2938***
	(0.1292)	(0.0858)
Constant	0.0986***	0.0725***
	(0.0027)	(0.0018)
Observations	109	109
R^2	0.0226	0.0988

Standard errors in parenthesis. ***Significant at 1%. **Significant at 5%. *Significant at 10%.

of the change in its relative price. Exploiting this restriction, Cummins and Violante (2002) computed time series of quality improvement – or technical change – for a variety or equipment goods over the period 1948–2000.

Using detailed data on capital expenditures by two–digit SIC industries provided by the Bureau of Economic Analysis, Cummins and Violante (2002) also constructed measures of investment–specific technological change by sector. In this section we ask whether such measures are systematically related to our proxies for risk.

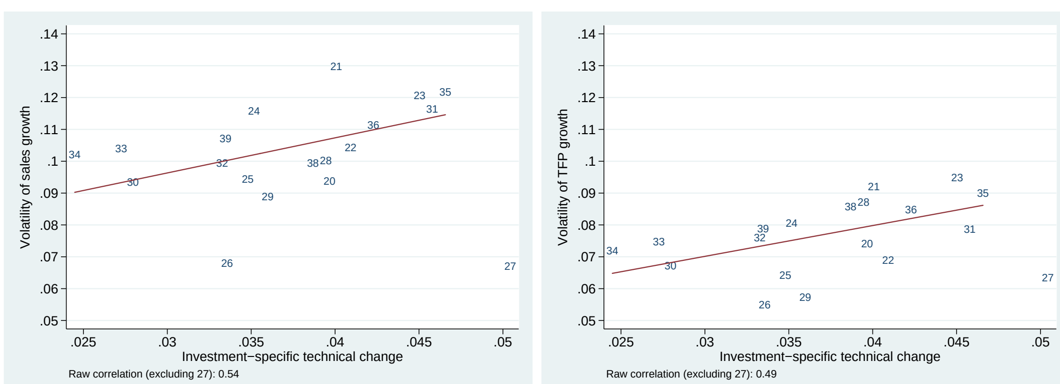

Figure 4: Idiosyncratic Risk and Investment–Specific Technological Change.

Given the level of aggregation in the data on technological change, our analysis is confined to 19 two–digit SIC sectors, listed in Table 6. For each industry, the rate of technological change is the average of the 1948–1999 annual time–series underlying Figure 2 in Cummins and Violante (2002), provided to us by Gianluca Violante. The risk proxies are weighted averages of the volatility estimates for the three–digit SIC sectors that belong to the industry. The weights are the values of the average share of each 3-digit sector's value of shipments in the corresponding two–digit sector.[9]

The scatter plots in Figure 4 suggest a positive association between the two variables. Sectors such as SIC 35 (Industrial and Commercial Machinery and Computer Equipment) and 31 (Leather and Leather Products) display high volatility and high investment–specific technological change. SIC 34 (Fabricated Metal Products, except Machinery and Transportation Equipment), which ranks last in terms of technological change, is also among the least uncertain sectors.

Table 3: Idiosyncratic Risk and Investment–Specific Technological Change.

Dependent Variable:	**Sales volatility**	**TFP volatility**
ISTC	1.1235**	0.9370**
	(0.5174)	(0.3767)
Constant	0.0997***	0.0417***
	(0.0627)	(0.0141)
Observations	18	18
R^2	0.228	0.279

Standard errors in parenthesis. ***Significant at 1%. **Significant at 5%. *Significant at 10%.
Note: SIC 27 excluded.

The magnitude and statistical significance of the correlation coefficients depends on an outlier observation, SIC 27 (Printing and Publishing). Given the small number of data–points, this is not surprising. Unfortunately we were not able to make sense of the finding that plants mostly engaged in the printing and publishing of books, periodicals, and newspapers experienced the fastest investment-specific technological progress.

When we exclude SIC 27, the raw correlations are 0.53 and 0.48 for TFP growth and sales growth, respectively. Both estimates are significantly different from zero at the 5% confidence level. When we include the outlier, the correlations drop to 0.33 and 0.13. Neither turns out to be significant at the 10% level.

Table 3 reports the results of regressing our proxies for idiosyncratic risk on a constant and the estimated speed of investment–specific technological change. When we drop SIC 27, a 1% increase in ISTC is associated with a 1.12% increase in the volatility of sales or a 0.93% increase in the volatility of TFP growth. Both estimates are significant at the 5% level.

[9]The averages are computed from the NBER manufacturing database, which covers the 1958-1997 period.

5 Consumption Vs. Investment Goods

CCM showed that in COMPUSTAT firms producing investment goods are significantly riskier than firms producing consumption goods. Does this pattern also holds across manufacturing firms in the LRD?

We classify industries as either consumption– or investment good–producing, based on the 1992 BEA's Use Input–Output Matrix. For every sector, the Use Matrix reports the fractions of its output that reach all other sectors as input, as well as the portions that meet final demand uses.

For each three–digit SIC industry, we compute the output share whose ultimate destination is either consumption or investment. We label an industry as "consumption" or "investment" if a sufficiently large share of its production ultimately meets a demand for consumption or investment, respectively. The outcome of our assignment procedure is in Table 5. The details of the algorithm are in Appendix A.2.

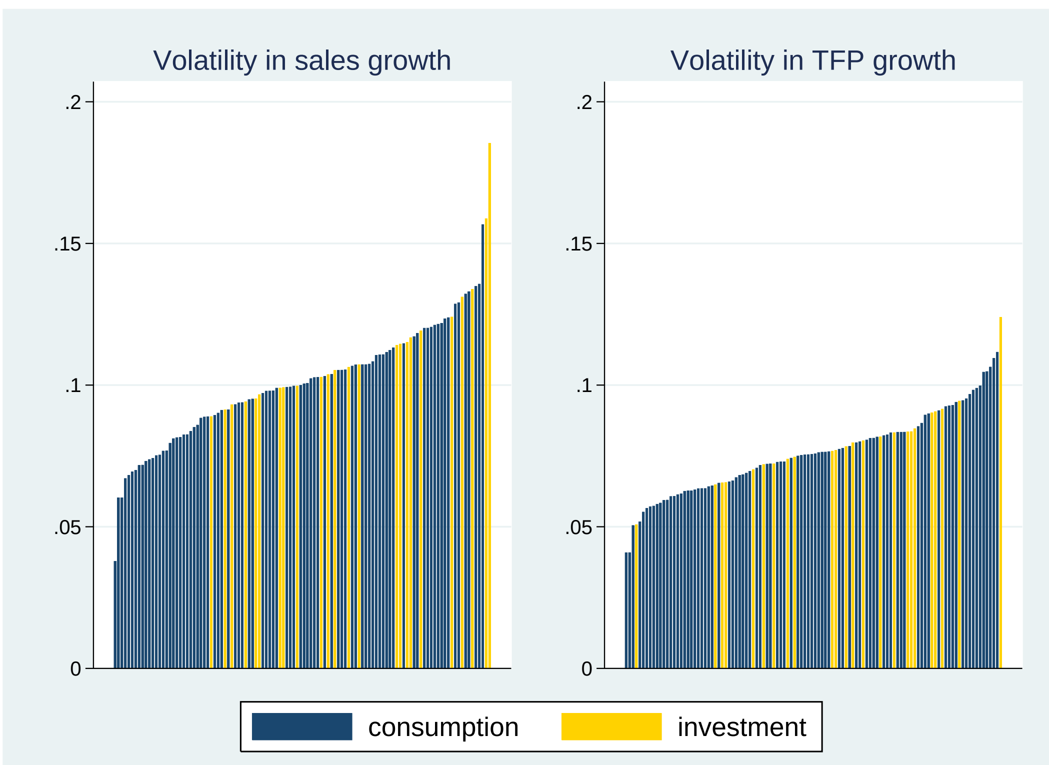

Figure 5: Volatility of sales growth per three–digit industry.

Figure 5 suggests a clear tendency for investment good sectors to be among the most volatile, no matter the proxy for risk. The height of each bar reflects the volatility of one three–digit sector.

In the case of sales growth, the outputs of the top two sectors are railroad equipment and computer equipment, respectively. The bottom 28 sectors fit in the consumption good category. Among them are Dairy Products (SIC 202), Bakery Products (205), as well as Books (123).

Computer equipment is also the most volatile sector when risk is proxied by the volatility of TFP growth. Only one investment–good sector – Wood Buildings (245) – is among the bottom 28 sectors in the ranking.

Formal tests confirm that on average investment–good producing firms are indeed more volatile. We run the following regression:

$$\ln \hat{\varepsilon}^2_{ijt} = \alpha + \theta_C + u_{ijt}, \tag{3}$$

where α is a constant and θ_C is a dummy variable which takes value 1 if firm i produces consumption goods and is zero otherwise. With sales growth, the point estimate of θ_C is -0.3624, different from zero at the 1% confidence level. The mean sales growth volatility among investment good–producing firms is 11.18%. For consumption good–producing firms it is 9.33%.

The message does not change when we consider TFP growth. The average volatility is 8.49% in investment good sectors and 7.62% in consumption good industries. We can reject the hypothesis that the two estimates are equal at the 1% confidence level.

Table 4: Idiosyncratic Risk and Durability

Dependent Variable:	Sales Growth	TFP Growth
Non-Durable Cons. Dummy	–0.3963***	–0.1331***
	(0.024)	(0.0242)
Durable Cons. Dummy	–0.1621***	–0.1463***
	(0.0372)	(0.0365)
Constant	–4.3835***	–4.9361***
	(0.0137)	(0.0148)
Observations	446,837	428,888

Standard errors in parenthesis. ***Significant at 1%. **Significant at 5%. *Significant at 10%.

At business–cycle frequencies, the difference in volatility between aggregate consumption and investment expenditures is mostly driven by the difference in durability between the two good categories. In fact, expenditures on durable consumption goods are almost as volatile as investment expenditures. Does a similar pattern emerge at the firm level?

To test whether volatility co–varies systematically with durability, we run the regression

$$\ln \hat{\varepsilon}_{ijt}^2 = \alpha + \theta_D + \theta_{ND} + u_{ijt}, \tag{4}$$

where θ_D and θ_{ND} are dummy variables that take value 1 if the firm produces durable or non–durable consumption goods, respectively.

We classify consumption goods as durable if they have a service life of 3 years or more, and nondurable otherwise. The service life data is from Bils and Klenow (1998). We drop sectors for which they do not provide information. The details of the assignment procedure are in Appendix A.3. The regression's results are reported in Table 4.

On average, firms producing nondurable consumption goods have a standard deviation of sales growth of 9.17%, lower than the estimate we obtained for the consumption sector as a whole. However, when we consider TFP growth we find no appreciable difference in volatility between firms producing durable and non–durable consumption goods.

No matter the proxy, estimated risk in sectors producing durable consumption goods is statistically and economically lower than in investment good sectors. The bottom line is that we found no evidence in support of the claim that durability is the reason why investment–good producing firms bear a greater idiosyncratic risk than firms producing consumption goods.

6 Conclusion

In the recent but fast growing theoretical literature on firm dynamics, heterogeneity in outcomes is often driven by idiosyncratic shocks. Yet, very little is known about the magnitude and cross–sectoral variation of such disturbances. This paper makes some progress towards understanding both.

Using a large panel representative of the entire US manufacturing sector, we found that idiosyncratic risk accounts for about 90% of the overall uncertainty faced by firms. We also showed that risk varies greatly across three–digit sectors. The portion of volatility in TFP growth that we cannot ascribe to aggregate factors is as small as 4.09% for producers of fur goods and as high as 12.4% for producers of computer equipment. The cross–sectoral variation is even larger when we use sales growth *in* *lieu* of TFP growth.

We propose that the heterogeneity in idiosyncratic risk may be driven by the differential extent to which creative destruction shapes competition across sectors. Formal models of Schumpeterian competition imply a positive correlation between the speed of technological progress, product turnover, and volatility in firm–level outcomes. We provide evidence in support of these predictions. In particular, our proxies for idiosyncratic risk are positively associated with measures of product turnover and investment–specific technological change, respectively.

A Data and Measurement

A.1 Variable Definitions

Real Sales or Output. We use the total value of shipments (TVS) deflated by the four–digit industry-specific shipments deflator from the NBER manufacturing productivity database. Although it is possible to adjust total shipments for the change in inventories, we follow Baily, Bartelsman, and Haltiwanger (2001) in imputing inventories for some plants (in particular, the smaller ones). To avoid potential measurement issues associated with this imputation, we focus on gross shipments.

Capital. We follow Dunne, Haltiwanger, and Troske (1997) closely in constructing capital stocks. The approach is based on the perpetual inventory method. We define the initial capital stock as the book value of structures plus equipment, deflated by the BEA's two–digit industry capital deflator. In turn, book value is the average of beginning-of-year and end-of-year assets. The investment series are from the ASM, deflated with the investment deflators from the NBER manufacturing productivity database (Bartelsman and Gray, 1996). Two–digit depreciation rates are also obtained from the BEA.

Labor input. The labor input is measured as the total hours of production and nonproduction workers. Since the latter are not actually collected, we follow Baily, Hulten, and Campbell (1992) in assuming that the share of production worker hours in total hours equals the share of production workers wage payments in the total wage bill.

Materials. The costs of materials are deflated by the material deflators from the NBER manufacturing productivity database.

Factor Elasticities. We use four–digit industry–level revenue shares as factor elasticities. This procedure implicitly assumes that all plants in each narrowly defined industry operate the same production technology, a common assumption in the literature on plant–level productivity. In calculating labor's share of total costs, we follow Bils and Chang (2000) and adjust each four–digit industry's wage and salary payments by a factor that captures all the remaining labor payments, such as fringe benefits and employer Federal Insurance Contribution Act (FICA) payments. This factor is based on information from the National Income and Product Accounts (NIPA), and corresponds to one plus the ratio of the additional labor payments to wages and salaries at the two–digit industry level. We apply the same adjustment factor to all firms within the same two–digit industry.

ASM sample weights. For all plant–level regressions, we use the ASM sample weights, which render the ASM a representative sample of the population of manufacturing plants (Davis, Haltiwanger, and Schuh, 1996).

A.2 Definition of Consumption and Investment Categories

To assign sectors to the consumption and investment categories, we rely on the Bureau of Economic Analysis' (BEA) 1992 Benchmark Input–Output Use Summary Table (before redefinitions) for six–digit transactions. The 1992 Use Table is based on the 1987 SIC system, and thus compatible with the ASM.

The Use Table gives the fraction of output that each three–digit sector supplies to every other three–digit industry, as well as directly to final demand uses. The final demand uses correspond to NIPA categories. For each three–digit industry j, we define its final demand for consumption $C(j)$ as the sum of personal, federal, and state consumption expenditures. The final demand for investment $I(j)$ is defined analogously. We exclude imports, exports, and inventory changes from our definitions, since they are not broken down into consumption and investment. Let C and I denote the vectors of all the industries' final consumption and investment expenditures, respectively.

From the Use Table, we also compute the (square) matrix A of unit input–output coefficients. This matrix can be easily constructed from the original Use Input–Output Matrix by normalizing each row by the total commodity column. We can then define the vectors of all the industries' total consumption and total investment output by

$$Y_C = AY_C + C \Leftrightarrow Y_C = (I - A)^{-1} C$$

and

$$Y_I = AY_I + I \Leftrightarrow Y_I = (I - A)^{-1} I,$$

respectively. This means that each industry's consumption goods output also includes all the intermediate goods whose *ultimate* destination is final consumption. Similarly, for investment.

For each three–digit industry j, we compute the share of output destined to consumption, $Y_C(j)/\left(Y_C(j) + Y_I(j)\right)$. We then assign all industries with a share greater than or equal to 60% to the consumption good sector, and those with a share lower than or equal to 40% to the investment good sector. We discard the remaining industries.

We also discard industries whose primary role is supplying intermediate inputs to other industries. That is, we drop three–digit industries which contribute less than 1% of their total output directly to final consumption and investment expenditures.

A.3 Definition of Durable and Nondurable Consumption Categories

When splitting consumption sectors between durable and nondurable, we follow Bils and Klenow (1998). Table 2 of their study reports the service life of 57 consumption good items (those in the Consumer Expenditure Surveys that closely match four–digit SIC sectors). Their estimates are either based upon life expectancy tables from insurance adjusters, or upon the Bureau of Economic Analysis publication *Fixed Reproducible Tangible Wealth, 1925–1989*.

We classify goods as either durable on nondurable, depending on whether their expected lives are longer or shorter than 3 years. We classify each three–digit sector as producing durables or nondurables, according to the weighted average of its four–digit sub–sectors' expected lives. Finally, we drop those three–digit sectors that are not considered in Bils and Klenow (1998).

B Tables

Table 5: Volatility Estimates

SIC		Sales Growth	Ranking	TFP Growth	Ranking
		Investment Sectors			
243	Millwork	0.10280	62	0.06554	103
245	Wood Buildings	0.13110	13	0.05076	130
252	Office Furniture	0.09415	89	0.07019	88
254	Shelving & Lockers	0.10374	59	0.07390	77
259	Misc. Furniture	0.10632	51	0.07670	62
324	Cement, Hydraulic	0.08890	103	0.08350	37
325	Clay Products	0.09898	75	0.08172	47
327	Concrete & Plaster	0.11510	32	0.07967	55
328	Stone Products	0.10721	48	0.09065	25
343	Heating Equipment	0.09128	97	0.06487	105
344	Metal Products	0.11675	31	0.07699	61
352	Farm Machinery	0.12404	16	0.07832	57
353	Construction & Mining	0.13379	9	0.08360	36
354	Metalworking Machinery	0.10524	56	0.08463	34

Table 5: (continued)

SIC		Sales Growth	Ranking	TFP Growth	Ranking
355	Special Industry Machinery	0.11449	34	0.08322	41
356	General Industry Machinery	0.09665	83	0.07220	81
357	Computer Equipment	0.15876	2	0.12395	1
358	Refrigeration Machinery	0.09309	94	0.06565	102
361	Electr. Distrib. Equipment	0.09918	74	0.07199	84
362	Electrical Apparatus	0.09969	70	0.07462	75
366	Communication Equipment	0.11918	26	0.09439	15
374	Railroad Equipment	0.18537	1	0.09023	26
381	Navigation Equipment	0.11408	35	0.09154	22
382	Measuring Instruments	0.09520	86	0.08039	52
	Durable Consumption Sectors				
227	Carpets & Rugs	0.10379	58	0.06267	113
231	Men's Suits & Coats	0.11826	27	0.09100	24
251	Household Furniture	0.08932	102	0.05710	126
273	Books	0.07374	123	0.06419	107
274	Misc. Publishing	0.07167	126	0.08340	38
316	Luggage	0.11053	42	0.08945	28
322	Glass & Glasware	0.07177	125	0.05942	121
348	Small Arms & Ammo	0.12910	14	0.10458	8
363	Households Appliances	0.10724	46	0.07423	76
365	Households Audio-Video	0.12339	18	0.09520	13
375	Motorcycles, Bicycles	0.12012	24	0.09396	16
379	Misc. Transportation	0.13299	11	0.06957	90
385	Ophthalmic Goods	0.09895	76	0.09457	14
387	Watches, Clocks	0.11230	37	0.07968	54
391	Jewelry & Silverware	0.10831	44	0.08127	49
393	Musical Instruments	0.08243	113	0.06352	109
394	Dolls, Toys, & Games	0.11467	33	0.08337	40
	Nondurable Consumption Sectors				
202	Dairy Products	0.07950	117	0.05650	127
203	Canned Fruits & Vegetables	0.10232	66	0.07838	56
204	Grain Mill Products	0.09375	92	0.07213	83
205	Bakery Products	0.06991	127	0.06070	119
206	Sugar	0.09798	77	0.07500	73
207	Fats & Oils	0.12118	21	0.09674	12
208	Beverages	0.09384	91	0.07738	60
209	Misc. Food	0.10673	50	0.09245	21

Table 5: (continued)

SIC		Sales Growth	Ranking	TFP Growth	Ranking
212	Cigars	0.09491	88	0.06254	115
213	Chewing Tobacco	0.07677	118	0.08065	51
225	Knitting Mills	0.12179	19	0.08169	48
232	Men's Clothing	0.12381	17	0.09891	10
234	Women's Underwear	0.10716	49	0.09287	19
236	Girls' Outerwear	0.12010	25	0.10478	7
271	Newspapers: Publishing	0.03780	133	0.05047	131
272	Periodicals: Publishing	0.07673	119	0.07291	79
283	Drugs	0.10269	65	0.09825	11
284	Detergents & Cosmetics	0.09316	93	0.07635	65
291	Petroleum Refining	0.08590	108	0.05521	128
299	Misch. Petroleum	0.09132	96	0.06841	96
301	Tires	0.08837	106	0.06074	118
314	Footwear	0.12151	20	0.07772	59
	Other Consumption Sectors (no service life information)				
214	Tobacco Stemming	0.15666	3	0.09972	9
221	Cotton Fabric	0.10063	67	0.07074	87
222	Silk Fabric	0.08886	104	0.05795	124
223	Wool Fabric	0.09795	78	0.07520	72
224	Narrow Fabric	0.08507	110	0.06589	101
226	Dyeing Textiles	0.11155	39	0.07652	63
228	Yarn & Thread Mills	0.10274	64	0.06134	117
229	Misc. Textile Goods	0.09926	73	0.07291	78
233	Women's Outerwear	0.13566	7	0.10947	5
235	Hats & Caps	0.10723	47	0.08120	50
237	Fur Goods	0.06940	128	0.04087	133
238	Misc. Apparel	0.12047	22	0.09271	20
239	Misc. Textiles	0.10541	53	0.07578	67
244	Wood Containers	0.09968	71	0.06894	92
249	Misc. Wood Products	0.10526	55	0.07621	66
261	Pulp Mills	0.07413	122	0.07279	80
262	Paper Mills	0.06812	129	0.05839	123
263	Paperboard Mills	0.06706	130	0.06347	111
265	Paperboard Containers	0.06024	131	0.04087	132
267	Converted Paper Products	0.07314	124	0.05732	125
275	Commercial Printing	0.07514	121	0.06162	116
276	Business Forms	0.06022	132	0.05176	129
277	Greeting Cards	0.08253	112	0.08657	30
278	Bookbinding	0.07535	120	0.06266	114

Table 5: (continued)

SIC		Sales Growth	Ranking	TFP Growth	Ranking
279	Services for Printing	0.08157	114	0.08247	44
281	Inorganic Chemicals	0.11076	40	0.10638	6
282	Plastic Materials	0.09113	98	0.07219	82
286	Organic Chemicals	0.09712	81	0.08541	32
287	Agricult. Chemicals	0.13484	8	0.11162	4
289	Misc. Chemicals	0.10044	68	0.08320	42
302	Rubber Footwear	0.13218	12	0.08337	39
305	Packing Devices	0.08365	111	0.07169	85
306	Rubber Products	0.08877	105	0.06351	110
308	Misc. Plastic Products	0.09511	87	0.06815	97
311	Leather Finishing	0.11066	41	0.07547	70
313	Shoe Cut Stock	0.11712	28	0.05930	122
315	Leather Gloves	0.10528	54	0.08004	53
317	Handbags	0.12864	15	0.08220	45
319	Other Leather Goods	0.10306	61	0.08991	27
321	Flat Glass	0.09015	100	0.07555	68
323	Glass Products	0.09988	69	0.06740	99
341	Metal Cans	0.09936	72	0.06542	104
342	Cutlery	0.08111	116	0.06443	106
346	Metal Forging	0.09790	80	0.06303	112
369	Electrical Equipment	0.10743	45	0.07637	64
395	Pens & Pencils	0.08148	115	0.06620	100
396	Buttons & Needles	0.11319	36	0.07537	71

Table 6: 1987 SIC

SIC	Description
20	Food and Kindred Products
21	Tobacco Products
22	Textile Mill Products
23	Apparel
24	Lumber and Wood Products
25	Furniture
26	Paper Products
27	Printing and Publishing
28	Chemicals
29	Petroleum Refining
30	Rubber and Miscellaneous Plastics Products
31	Leather and Leather Products
32	Stone, Clay, Glass, and Concrete Products
33	Primary Metal Industries
34	Fabricated Metal Products, except Machinery and Transportation Equipment
35	Industrial and Commercial Machinery and Computer Equipment
36	Electronic and Other Electrical Equipment, except Computer Equipment
38	Instruments and Related Products
39	Miscellaneous Manufacturing Industries

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